DOCUMENT RESUME

ED 414 656 EA 028 844

AUTHOR	Kang, Sang-Jin
TITLE	Multilevel Models for Studying Organizational Transition Effects.
PUB DATE	1997-03-00
NOTE	25p.; Paper presented at the Annual Meeting of American Education Research Association (Chicago, IL, March 23-28, 1997).
PUB TYPE	Numerical/Quantitative Data (110) -- Reports - Research (143) -- Speeches/Meeting Papers (150)
EDRS PRICE	MF01/PC01 Plus Postage.
DESCRIPTORS	*Adolescent Development; Equations (Mathematics); Factor Analysis; Grade 10; Grade 8; *Longitudinal Studies; Middle Schools; Models; *Multitrait Multimethod Techniques; *Multivariate Analysis; Secondary Education; Self Esteem; Statistical Analysis; Tables (Data)
IDENTIFIERS	National Education Longitudinal Study 1988

ABSTRACT

Over the past 15 years a body of research has investigated organizational transitions in adolescent development. Researchers studying school transitions exclusively ask whether significant transition affects students' social and psychological development. To test the presence of transition effects, researchers have typically observed mean differences on certain observed outcomes between the students who experienced school transition and those who did not. This paper shows that much more could be learned about organizational transitions if investigators change their operational definition of transition effects from "mean difference" to "an effect being in a transition group." The new definition changes the research question from "whether" to "how much," and accounts for the uncertainties of transition effects as well as the outcome under investigation by multilevel modeling. The paper demonstrates multilevel modeling by analyzing longitudinal data from NELS:88 to identify the effects of between-school transitions on student self-esteem. The final sample for this paper was composed of 483 students in 100 middle schools and 113 high schools, who were observed at the 8th and the 10th grades. The analyses show the estimates of transition effects and identify the components of transition effects, the effects of individual background variables, past and present organizational characteristics, and the interaction effects between past and present organizations. Multilevel modeling also allows investigation of the interaction effects between individual backgrounds and school characteristics. Twelve tables and 3 figures are included. (Contains 19 references). (LMI)

Multilevel Models for Studying Organizational Transition Effects

Sang-Jin Kang
Yonsei University, Seoul

Paper presented at the annual meeting of AERA
March 23 - 28, 1997, Chicago, Ilinois

Over the past fifteen years, there has been a body of research studying organizational transitions in the literature on adolescent development. Researchers studying school transitions exclusively ask whether significant transition effects on various social and psychological development of students' motives, beliefs, and behaviors exist. To test the presence of these transition effects, researchers typically designed their studies to observe mean differences on certain observed outcomes between the students who experienced school transition and students who did not (For example, Crockett, et al., 1989).

In this study, I will show that much more could be learned about organizational transitions if investigators change their operational definition of transition effects from mean difference to an effect being in a transition group which is striatforward in statistical modeling. This new definition of transition effects will lead researchers to change their research questions from whether to how much, and attempt to account for the uncertainties of transition effects as well as the outcome under investigation by multilevel modeling. I will demonstrate multilevel modeling by analyzing longitudinal data from NELS:88 study for the effects of between-school transitions on student self-esteem, where students were observed at eighth and tenth grade. The analyses will show (a) the estimates of transition effects, and explicit (b) the components of transition effects. The methods will also explain the variability of transition effects in terms of: (c) the effects of individual background variables, (d) past organizational (i.e., school) characteristics, (e) present organizational characteristics, and (f) the interaction effects between past and present organizations. Multilevel modeling also allows us to investigate the interaction effects between individual backgrounds and school characteristics.

The Problem

The reason why transition studies have attempted to address the questions of 'whether' rather than 'how much' is not certain. I, however, would point out that the reason is rooted in the choice of statistical methods. Studies on educational transition typically employed the techniques of ANOVA or ANCOVA (Midgeley & Feldlaufer, 1987; Jones & Thornburg, 1985), multivariate Analysis of Covariance (Hirsh & Rapkin, 1987; Crockett, et al., 1989), and Ancova via regression modeling (Simmons, et al., 1979). By engaging in the analyses of means, researchers implicitly define transition effect as significant mean difference in an outcome before and after transition or between students who experienced transition and who did not. Such a definition ignores the situation when no significant mean differences were found even though transition had actually occurred. The variability of transition effects across schools and other social units, within which students are nested, cannot be accounted for via the fixed-effects modeling.

On the other hand, transition studies have largely ignored the issues of unit of analysis. Transition data are inherently hierarchical. Students are nested within each of many schools before and after the transition. When variables were measured at different levels of observations in hierarchical data, hypothesis testing based on individual observation is questionable since it violates independence assumption (Cronbach, 1976; Hopkins, 1982). An alternative choice of group-level analysis, in order not to violate the assumption, often commits ecological and aggregation bias (Robinson, 1950; Burstein, 1980). An appropriate analytical method then should allow the model specification that accounts for the structure of data, where students are nested within previous and present schools, and also guides the research inquiry. Until recently, sound statistical methods for transition data and for answering the 'how much' question have not appeared in the literature on statistical methods.

Classical Methods

Although there has been a body of research studying the effects of organizational transitions on adolescent development, it is hard to find methodological studies on the effects of organizational transitions. Researchers in this field designed their study in sophisticated ways, however, they implicitly defined the transition effects in two ways based on their study design. The first is, when they had cross-sectional data, within which subjects were classified into subgroups that represent different transition types. Then they estimated transition effects by showing the mean difference between the subgroups and tested their hypothesis of no difference. For example, researchers compared the groups that represented a different number of transitions and transition timing (Simmons, Rosenberg, and Rosenberg, 1973; Crockett, et al, 1989). In order to estimate the transition effects in those designs, researchers often use Anova for data analysis. To show the implicit definition of transition effects in Anova model, write,

$$(1) \qquad Y_{ijk} = \mu + \alpha_j + \beta_k + \alpha\beta_{jk} + e_{ijk}, \quad e_{ijk} \sim N(0, \sigma^2),$$

which shows two main factors (α_j, β_k) and their interactions ($\alpha\beta_{jk}$). Let's say that the first factor indicates the effect of transition groups, coded "1" for a group of students who changed their school memberships, and coded "2" for a group of students who did not change school memberships. Again assume the second factor is sex variable, coded "1" for female and "2" for male students. Given the model, there are three hypotheses;

$$
\begin{aligned}
(2) \qquad & H_0\text{: } \mu_{1.} - \mu_{2.} = 0 \\
& H_0\text{: } \mu_{.1} - \mu_{.2} = 0 \\
& H_0\text{: } \mu_{11} - \mu_{21} = \mu_{12} - \mu_{22}
\end{aligned}
$$

It is clear that the hypotheses are of no mean differences between transition groups, and between male and female students, plus no interaction effects across the cells defined by the cross-classification of the two main factors in the outcome measure. When researchers rejected the first hypothesis, they interpreted it as the evidence of transition effect on the outcome measure, by saying that students who changed their schools (i.e., j=1) show more or less a mean outcome value than the students who did not (i.e., j=2). The third hypothesis of interaction effects shows the evidence of transition patterns by showing whether the mean difference between transiton groups for females (k=1) is the same as for males (k=2).

On the other hand, when researchers had longitudinal data, they employed within-subject design or split-plot design for data analysis. Midgeley and Feldlaufer (1987) compared their outcome means before and after transition. Jones and Thornburg (1985) used split-plot design where pre- and post-measures made one within-subject factor and sex and different type of transition groups were two between-subject factors. Hirsch & Rapkin (1987) examined multiple outcomes via Manova using repeated design, where they compared the mean scores at each observation time via contrasts. To simplify the model presentation, suppose there are one within-subject factor as pre- and post-measures, and only one between-subject factor, say sex. The Anova model for this design is,

$$(3) \qquad Y_{ijk} = \mu + \alpha_j + \beta_k + \pi_i + \alpha\beta_{jk} + e_{ijk}, \quad \pi \sim N(0, \sigma_\pi^2), \quad e_{ijk} \sim N(0, \sigma_e^2)$$

where μ is the grand mean; α_j is the effect of sex coded "1" for males "2" for females; β_k is the time (i.e., transition) effect coded "1" for pre-observation, "2" for post-observation; π_i is the effect of i_th individual (or blocks); $\alpha\beta_{jk}$ is the interaction effect between sex and observation times; e_{ijk} is the error. The model typically assumes that there are no interaciton effects between the effects of subjects (or blocks; π_i) and observation time (β_k). The transition effects in this design is the effect of observation time (i.e., β_k). The null hypothesis is,

(4) $$H_0: \mu_{..1} - \mu_{..2} = 0.$$

The hypothesis simply means the mean difference in an outcome measured before and after transition.

Another way of investigating transtion effects is to use the Regression technique, where prior measure of an outcome is used as a covariate and a series of dummy predictors are used to indicate each of the subgroups that represent different type of transitions, from which researchers tested whether the estimated effects of dummy predictors were zero or not (Blyth, et al., 1978; Simmons, et al., 1979). Suppose there is only one dummy indicator coded "1" for the students who changed their schools and "0" for the students who did not. Suppose again that there are covariates other than the prior measure of outcome variable. The regression model, then, takes the form as below;

(5) $$Y_i = \beta_0 + \beta_1(prior\ score)_{i1} + \sum_{p=2}^{p=P-1} \beta_p(Covariate)_{ip} + \beta_P D_{iP} + e_i,$$
$$e_i \sim N(0, \sigma^2).$$

where Y_i is the post observation of outcome variable for person i ; β_1 to β_{P-1} are the structural relationship between the covariates and the outcome measure after accounting for the effects of the other variables in the model. The effect of D_{iP}, β_P, is the adjusted mean difference between the students who transitioned and who did not, after accounting for the effects of prior score and the other covariates. The hypothesis for testing transition effect in this model is,

$$H_0: \beta_P = 0.$$

Since the dummy predictor, D_{iP}, is coded "1" and "0", the meaning of the hypothesis is the same as,

(6) $$H_0: \mu_1 - \mu_0 = 0,$$

where μ_0 is the adjusted mean of the non-transitioned group, which is β_0 in the model, and μ_1 is the adjusted mean of the transitioned group, which is $\beta_0 + \beta_1$. So the two hypotheses are equivalent.

As briefly examined the analytical approches to the effects of transitions on students' developmental characteristics, those researchers who employed the techniques of ANOVA, ANCOVA, MANOVA, or Regression methods for data analysis estimated the transition effects as

the mean difference between the subgroups or the mean difference between before and after transition. Statistically, the transition effects here are assumed to have fixed effects, which lead researchers to test the hypothesis whether transition effects exist or not. The large mean difference between transition subgroups or between the measures before and after transition does not show strong transition effect in statistical hypothesis testing. It is used to find the probability to observe such a large mean difference when the hypothesis of no mean difference in population is true. In other words, it shows only that there is a chance whether there exists mean difference in population. Researchers may compute effect-size to show the practical meaning of the size of observed mean difference. If the effect-size is still large, they would say that there are large transition effects on average. This statement does not account for the differences in transiton effects among individuals who experienced transitions, since the finding is only informative as an average.

On the other hand, when researchers fail to reject their null hypothesis, they would say there is no sufficient evidence for transition effects. Suppose the null hypothesis is actually true, saying there is no mean difference between transition group means or before and after transtions. Researchers using classical methods in this situation would stop their analysis and report no finding. However, it would not be reasonable to say that transitions do not have any effects on the students developmental characteristics under study. It is quite possible that the effects of transitions on students' developmental characteristics can vary widely while the mean values are zeros.

Multilevel Approach

Researchers in the field of school transition studyies mainly concerned with developmental characteristics of young adolescents. To study the transition effects on adolescents' traits, they designed studies and collected data from the students attending schools. In school settings, students are grouped into classes to learn, and these classes are the subunits within schools. We call this a hierarchical structure. It is well known to researchers in the field of school effects that school data tends to have hierarchical structure and that analyzing hierarchical data often leads to the problems of unit of analysis, as well as, other problems of controling the effects of confounding variables, aptitude by treatment interactions (see, Burstein, 1980; Bryk and Raudenbush, 1992).

Statistical advances in the analysis of hierarchical data allow researchers to develop softwares that are now flexible enough for modeling hierarchical data (de Leeuw and Kreft, 1986; Goldstein, 1986; Aitkin and Longford, 1986; Raudenbush and Bryk, 1986). To demonstrate the estimation of transition effects, I used a newly developed crossed- multilevel model (Raudenbush, 1993; Rasbash and Goldstein, 1994; Kang, 1992).

To define the transition effects, I first begin by describing the crossed-multilevel model. In particular, this statistical model uses two types of classification factors, such as middle and high schools. The cross-classification of the two factors defines the cells (i.e., transition groups) within which students share the same memberships in previous and present schools. To understand the logic of the model in practice, consider Y_{ijk} is the score of an outcome (i.e., self-esteem) for child i in middle school j and high school k. This model takes the cells as the distinctive social units. So we first pose the model for each of the transition groups (the cells).

$$(7) \qquad Y_{ijk} = \beta_{0jk} + \beta_{1jk}X_{1ijk} + \beta_{2jk}X_{2ijk} + \ldots + \beta_{P-1jk}X_{P-1ijk} + e_{ijk}.$$

Equation (7) shows that an individual outcome (Y_{ijk}) score is predicted by p=1, . . . , P-1

individual background variables, X_{ijk}, with residual error, $e_{ijk} \sim N(0, \sigma^2)$. If the background variables, X_{ijk}, are centered around the grand means of the data, then the estimates of the intercepts, β_{0jk}, are the background-adjusted transition group means.

β_{0jk} will vary across the transition groups (cells), middle schools (past organizations), and high schools (present organizations). Suppose β_{0jk} are predicted by those school characteristics (W_1, W_2) and their interactions. We write

$$(8) \qquad \beta_{0jk} = \gamma_{00} + \gamma_{01} W_{1j} + \gamma_{02} W_{2k} + \gamma_{03} W_1 * W_{2jk} + a_{0j} + b_{0k} + c_{0jk}.$$

Equation (8) has three residual random effects: the effect of middle school j (a_j), high school k (b_k), and transition group (c_{jk}). They have mean zero and variances τ_a, τ_b, and τ_c respectively. If the predictors are centered around their means, then γ_{00} becomes the grand mean of self-esteem. The transition effect can be described as the effect being in a particular transition group, which is defined as,

$$(9) \qquad T_{jk} = \beta_{0jk} - \gamma_{00} = \gamma_{01} W_{1j} + \gamma_{02} W_{2k} + \gamma_{03} W_1 * W_{2jk} + a_{0j} + b_{0k} + c_{0jk}$$

Equation (9) shows that the transition effect being in a particular transiton group adjusted by individual backgrounds includes control for the effects of past and present organizational characteristics, and their interactions, plus the three components of random effects. The amount of transition effect can be measured by its variabiliity.

$$(10) \qquad \begin{aligned} Var(T_{jk}) &= \tau_a + \tau_b + \tau_c + C, \\ C &= Var(\gamma_{01} W_{1j} + \gamma_{02} W_{2k} + \gamma_{03} W_1 * W_{2jk}). \end{aligned}$$

Equation (10) will be the marginal transition effect if there are no predictors in Equation (7) and (8) for cross-sectional data. If one takes into account the effect of prior level of self-esteem (i.e., outcome variable) only at Equation (7), then Equation (10) will be net-marginal transition effect. Iterative process of model-building and interpretations will allow investigators to observe the changes in the three components of transition effects, τ_a, τ_b, and τ_c.

In a school effect study, Willms and Raudenbush (1989) presented type-A and type-B school effect, where type-A effect includes the effects of student body composition of a school, and the effects of school policies and practices plus random school effect. Thus parents would be interested in the information of type-A effect of a school. type-B effect is composed of the effects of school policies and practices and random effects. So school administrators and teachers would be interested in it. The crossed-multilevel model allows researchers to estimate all the components of transition effects respectively. It also allows for the estimation of the realized values of T_{jk}, and performs hypotheses testing for both fixed effect (γ) and each of the three random effects. Thus we can also present the types of transition effects in a similar way. Suppose the between-transition group model takes the form as,

$$\beta_{0jk} = \gamma_{00} + \gamma_{01}C_j + \gamma_{02}C_k + \gamma_{03}P_j + \gamma_{04}P_k + a_j + b_k + c_{jk},$$

where C_j and C_k are the student body compostion of middle school j and high school k. P_j and P_k are the policy variables for school j and k respectively. We can define the type-A transition effect as,

$$T_{Ajk} = \beta_{0jk} - \gamma_{00} = \gamma_{01}C_j + \gamma_{02}C_k + \gamma_{03}P_j + \gamma_{04}P_k + a_j + b_k + c_{jk.}$$

When parents face to their student transition they may look for the information about type-A effect of a particular school. Similarly, we may define type-B transition effect as,

$$T_{Bjk} = \beta_{0jk} - \gamma_{00} - \gamma_{01}C_j - \gamma_{02}C_k = \gamma_{03}P_j + \gamma_{04}P_k + a_j + b_k + c_{jk.}$$

Type-B transition effect would be more interested in school administrator since the transition effect is adjusted for the students intakes and contextual effects beyond their control.

Data and Variables

To illustrate this method for testing the general hypothesis in the context of study of student transitions to high school, data for the study was drawn from the NELS:88 longitudinal cohort. NELS:88 data base contains information about the psychological and academic developmenrt of ever 17,000 students in the United States. It also looks at the organizatoinal characteristics of the schools attened by these students in grades 8 and 10. The students in the NELS:88 longitudinal cohorts have experienced a variety of school transitions over the course of the study. To simplify the analysis of school transtions, I decided to use self-esteem as an outcome variable, and built a small sample of students. The sample included only those students who made transitions during the period of grade 8 and grade 10. So the students who attended those middle schools whose grades configuration include both 8th and 10th grades were excluded from the sample.

Students showed different patterns of missing variables and extreme values in the data. Students who provided incomplete data for any of the component items of the measures of self-esteem in this study were dropped from the sample. Those students who did not have school id information in the base year or first follow-up were also excluded. After data had been cleaned across all the variables to be used for demonstration, I sampled 100 middle schools. The final sample for demonstration included 483 students with 100 middle schools (base year), 113 high schools (first follow-up), and 133 cells defined by the cross classification of the two school memberships. The number of students within the cells ranged from 1 to 25.

Measures of Self-Esteem

Both base year and first follow-up data in NELS:88 have multiple items on self-esteem. I used factor analysis technique to indetify component items of the measure of self-esteem both in the base year and first follow-up data. Ten items that achieved the highest internal consistencies while keeping the coherent meanings of the items were found. In the base year the internal consistency was α = .78, and α = .81 for the self-esteem scale in the first follow-up data. All the components items were standardized and added up to make a composite scale. The names of

the components items of the two measures were presented in the Appendix.

Student level variables

Both base year and first follow-up data contained multiple student background variables. For demonstration purposes, two variables that were believed to be associated with change of self-esteem when students experienced school transitions were selected. They are sex and family composition. The sex variable showed balanced distribution and was coded "-1" for females and "1" for males. The family composition variables were categorized into two values as "1" for students from two parent families, and "0" for single parent or two parents with natural father only. The variable was then centered around its grand mean. Thus a negative value indicates mainly the students with a single parent families and a positive value indicates the students with two parent families. The summary of descriptive statistics for the individual level variables including the measures of self-esteem is shown in Table 1a.

(Table 1a is about here)

School level variables

NELS:88 data sets have separate school-level data sets both in the base year and in the first follow-up. The group-level variables that are considered as having contextual effects on students self-esteem were selected for demonstration purposes. Two variables of middle school characteristics were selected. These were the number of full time teachers (BYSC17) and grade configurations (G8TYPE). The grade configuration variable was then recoded into four dummy variables after excluded those students from the base year schools that included both grade 8 and 10. The length of average class (NF1C9) was selected as the high school characteristic, and the difference in school size (DSIZE) between students' base year schools and first follow-up schools was also selected as characteristics of the transition groups (cells). The summary of descriptive statistics for the school level variables appeare in Table 1b.

(Table 1b is abcut here)

Illustration

In order to demonstrate analyzing transition data using Crossed-Multilevel Models (here after referred to as, CMM), I will follow the general procedure of multilevel modeling, which is an effective way of showing the properties of CMM.

Estimation of Marginal Transition Effects

To measure the marginal transition effects, we first model the students' self-esteem in terms of their group memberships. In other words, we postulate that students' self-esteem is influenced by the schools they attended before (i.e., middle schools) and the schools they are now attending (i.e., high schools), and the interactions between the two schools. As I mentioned before, the students are nested within the cells classified by the two school memberships. So first, we model the student's self-esteem within each of the cells. We assume the students' individual self-esteem values are distributed around the cell mean. Therefore we write the within-transition group model as,

$$(12) \qquad Y_{ijk} = \beta_{0jk} + e_{ijk}, \quad e_{ijk} \sim N(0, \sigma^2),$$

where Y_{ijk} is the value of self-esteem of i_th students in middle school j and high school k; β_{0jk} is the mean of self-esteem of the students who attended j_th middle school and are now in k_th high school. We can say β_{0jk} is the mean of jk_th transition group (cell). e_{ijk} is random error. The means of transition groups, β_{0jk}, would vary around the grand mean due to the effects of middle schools, high schools, and their interactions. We write the between-transition groups model as,

$$(13) \qquad \begin{aligned} &\beta_{0jk} = \gamma_{00} + a_j + b_k + c_{jk}, \\ &a_j \sim N(0, \tau_a), \quad b_k \sim N(0, \tau_b), \quad c_{jk} \sim N(0, \tau_c) \end{aligned}$$

Equation (13) denotes γ_{00} as the grand mean, a_j as the effect of being in j_th middle school, b_k as the effect of being in k_th high school, and finally c_{jk} as the effect of particular a transition group (a cell). Those group effects are assumed to have normal distribution with mean zero and the specified variances. Equation (12) and (13) together make a crossed multilevel model. Table 2 below shows the results of data analysis via the model.

(Table 2 is about here)

Interpretations about the table will be done soon after I describe the transition effects.
From Equation (13) we define the marginal transition effects as,

$$(14) \qquad T_{jk} = \beta_{0jk} - \gamma = a_j + b_k + c_{jk}.$$

Then the amount of marginal transition effect is

$$(15) \qquad Var(T_{jk}) = \tau_a + \tau_b + \tau_c.$$

The estimation procedure in CMM uses EM algorithm and can produce the empirical Bayes estimates of random components in Equation (14). It also provides full maximum likelihood estimates of the components of transition effects in Equation (15). Table 2a presented below shows the summary of descriptive statistics of realized value of the terms in Equation (14).

(Table 2a is about here)

Now, let us consider the findings in Table 2, where the estimated variance at the within-transition group is 10.391, and the variances at middle school level is 3.254, at high school level is 3.19, and the variance at the transition group level after excluded the effects of middle and high schools is 3.998. From this results, the total between-transition group variance is $\hat{\tau}_a + \hat{\tau}_b + \hat{\tau}_c = 10.442$. About 50% of the total variance lies at the between-transition group level. So students' self-esteem values vary by individual differences ($\hat{\sigma}^2 = 10.391$) within each of the transition groups, which is 50% of the total variance. The remaining 50% is

attributable to the different transition group memberships, which is quite large. Here the total between-transition group variance is the size of marginal transition effects.

Table 2a shows the summary of descriptive statistics for the realized values (EB estimates) of the marginal transition effect and the component random effects of it at the transition group level. It shows the marginal transition effects ranges from −4.96 to 3.34. Figure 1 shows the histogram of the marginal transition effects.

(Figure 1 is about here)

It becomes clear from the figure that the transiton effects show a fairly normal distribution and there exists much variation in transition effects with some outliers. The traditional mean difference approach cannot account for the variability of transition effects across the social subunits (i.e., transition groups). Given the results of Table 2, Table 2a, and Figure 1, we now attempt to account for the variation of the transition effects.

Estimation of Net Transition Effects

As a first step, we need to estimate the net transition effects after accounting for student prior level of self-esteem. The method of CMM specification is very similar to the method of regression modeling. In this case, we use the self-esteem measured before students' transitions. Again students are nested within each of the transition groups, where students share their prior and current school memberships. For each of the students within each transition group, we write a within-transition group model.

$$(16) \qquad Y_{ijk} = \beta_{0jk} + \beta_1(BYESTEEM) + e_{ijk}, \quad e_{ijk} \sim N(0, \sigma^2)$$

where the mean value of BYESTEEM is about zero (see Table 1a). Thus β_{0jk} is the transition group mean of the outcome measure. The mean value for each of the transition groups would vary around the grand mean of the outcome. Also the structural relationship between self-esteem in base year and the outcome can vary too. I, however, set the parameter as having a fixed effect, which mean the effects of BYESTEEM on the outcome is the same across middle and high schools which may or may not true. Then the between-transition model can be made only for the intercept, which is the same as Equation (13). The results of analysis are shown in Table 3.

(Table 3 is about here)

The upper panel of Table 3 shows significant positive association between the prior and post measures of the self-esteem variable. The random effects are shown in the lower panel, where the within-transition group variance estimate is 9.872, and the between-transition group variance is decomposed into three parts: across middle schools, high schools, and transition groups. Comparing the results in Table 2, there is little change in those variance estimates. So we can see that there still exists substantive variation in student self-esteem even after accounting for the effect of prior level of self-esteem. The bottom of the table reports -2log(likelihood) value. The statistic can be used for a log-likelihood ratio test for testing the model improvement by comparing it with the one in Table 2, which will have χ^2 distribution with one degrees of freedom. The difference is 25.8575 and significant.

To compute the net transition effect, we use the same equation as Equation (14) and can

compute the size of transition effects by Equation (15). Below are the descriptive statistics of the residual random effects and the histogram.

(Table 3a and Figure 2 are about here)

In Table 3a, we can see that the results are not much different from the results in Table 2a. One can see, however, a general tendency of reduced range and variability even though they are not large. So we can see that much variation among the students across the transition groups still exists.

Estimation of Adjusted Transition Effects

The next step of analyzing transition effects is to account for the effects of student background variables that should be considered as given conditions in schooling. I included two student level covariates, sex and family composition. The model specification in this step is the same as in the previous step. We write the within-transition group model as

$$Y_{ijk} = \beta_{0jk} + \beta_1(BYESTEEM)_{ijk} + \beta_2(SEX)_{ijk} + \beta_3(FAMCOMP)_{ijk} + e_{ijk}, \quad e_{ijk} \sim N(0, \sigma^2). \tag{17}$$

In Equation (17) the predictors are again assumed to have fixed effects. Thus there is only one between-transition model for β_{0jk} , which again is the same model as Equation (13). From the model of Equation (17) one can obtain the same information as in the traditional approach. Researchers may test the hypothesis whether female students are more vulnerable to school transitions than male students. Similarly the effect of family composition on the adjusted change of self-esteem can be tested. The results of the analysis are given in Table 4.

(Table 4 is about here)

Table 4 shows that sex effect is marginally significant (t = −1.946) but the family compostion variable is not. The estimated beta weight of sex is −.278, which means that females showed lower self-esteem than males by twice the coefficient (.556) since the variable was coded "1" for males and "−1" for females. The results of random effects do not show a large difference from the previous results. The transition effects again takes the same form as before but it is adjusted by the individual background differences in the sample. Researchers using the traditional approach to the investigation of transition effects will do no further analysis. The CMM approach, however, allows for the examination of the transition effects more closely. To examine the transition effects directly, we can get the descriptive information of the random residuals. Table 4a shows the information of the adjusted transition effects, and the three components.

(Table 4a is about here)

Again the pattern of the results is similar to the previous results. Similarly we can visualize the distribution of transition effects as shown in Figure 3 below.

(Figure 3 is about here)

One can compare the distribution of adjusted transition effects with the one of marginal and of net transition effects. In this sample data, the analyses do not show much difference, which means the substantive transition effects are still uncertain.

Estimation of Type-A and Type-B Transition Effects

After researchers accounte for individual background variables, they can continue to examine the possible effects of school characteristics. For example, school transition often enforces young adolescents to face adjustment problems in a new school environment. Thus the environmental differences between middle and high schools are of interest in the next analysis. For demonstration of CMM analysis, I included three variables of middle school characteristics (BYSC17, G8LUNCH, G8TYPE), one high school variable (NF1C9), and one variable that shows environmental differences (DSIZE). Here the within-transition group model is the same as Equation (17), and between-transition group model is

$$\begin{aligned} \beta_{0jk} = \; & \gamma_{00} + \gamma_{01}(BYSC17)_j + \gamma_{02}(G8LUNCH)_j + \gamma_{03}(G8TYPE1)_j + \ldots \\ & + \gamma_{06}(G8TYPE4)_j + \gamma_{07}(NF1C9)_k + \gamma_{08}(DSIZE)_{jk} + a_{0j} + b_{0k} + c_{jk} \end{aligned} \tag{18}$$

with appropriate distributional assumptions of the residual parts as in the previous models. Equation (18) can provide information about the effects of middle and high school characteristics, and the effect of school size differences between high and middle schools on the adjusted mean of self-esteem. It also can show the residual random effects of middle schools, high schools and the transition groups. The results are shown in Table 5.

(Table 5 is about here)

Table 5 shows the results of fixed effects, as well as the random effects. In the upper panel of the table, the effects of the prior measure of self-esteem (byesteem) and of sex are approximately still the same. On the other hand, no group level variables other than G8TYPE3 were significant. G8TYPE variables are dummy coded with the default comparison group being the schools in which grades span from 6 or 7 to 9. It is hard to explain why significant adjusted mean difference between the middle schools with different grade configuration exist. It is also not a concern of the paper to explain why G8TYPE3 showed a significant effect. Table 5 shows the capability of CMM in providing such fixed effects information as the classical approach. Researchers using traditional analytical methods would stop the analysis since they got all the information about the effects of individual background variables and of school characteristics. Unlike the classical approach, CMM allows researcher to observe the transition effects directly via residuals. Table 5a shows the summary of descriptive statistics of realized values of group-level residuals, and type-A and Type-B transition effects.

(Table 5a is about here)

Here the type-A and type-B effects are

$$T_{Ajk} = \beta_{0jk} - \gamma_{00}$$

$$T_{Bjk} = \beta_{0jk} - \gamma_{00} - \gamma_{02}(G8LUNCH)_j$$

respectively. The type-A effect includes student body composition (G8LUNCH), and the contexual effects of number of teachers and of school size differences. It also includes the school practice of class length (NF1C9), and grade span variable. Since the transition group means, β_{0jk}, are adjusted only by student background characteristics, type-A transition effect has been adjusted only by individual background characteristics. Thus parents would be especially interested in this type of effect. On the other hand, type-B is adjusted by student intakes and contextual effects of student body composition. Thus the type-B effect would be interesting to school reform policy makers because it excludes the factors outside their control. Both type-A effect and type-B effect have distributions. Therefore, one can show relative standing of the effect by locating type-A and type-B effect of a particular transition group in the distribution.

Discussion

This paper attempted to change researchers' perspective of transition effects and showed CMM as an alternative methodological approach in studying organizational transitions. The analyses showed (a) the estimates of transition effects, and (b) the components of transition effects. The methods also explained the variability of transition effects in terms of: (c) the effects of individual background variables, (d) past organizational (i.e., school) characteristics, (e) present organizational characteristics, and (f) the interaction effects between past and present organizations. I hope the illustrative analysis can encourage researchers in this field to practice reframing their research inquiries and to perform multilevel analysis. In real research situations, the the number of schools and other social units may not be large, which may limit the advantages of multilevel modeling.

When the number of middle schools are large but high schools are not, we may treat the effects of high schools as fixed. Then we can specify the within-transition group model as Equation (7) and between-transition group model as

$$(11) \quad \beta_{0jk} = \gamma_{00} + \gamma_{01} W_{1j} + \sum_{k=2}^{K} \gamma_{0k} D_k + a_{0j} + c_{0jk}$$

where D_k are dummy variables indicating K-1 high schools or contrast variables. The variability of transition effects then can be estimated as

$$Var(T_{jk}) = \tau_a + \tau_c + C,$$

$$where \quad C = Var(\gamma_{01} W_{1j} + \sum_{k=2}^{K} \gamma_{0k} D_k)$$

Very often, transition studies can be performed with district level data, where the number of elementary schools and middle or high schools are relatively small. In this case, one may treat the transition groups (the cells) as distinctive social units for j = 1, 2, . . ., J, and employ the standard two-level hierarchical model. The iterative modeling process and interpretations on transition effects are consistent as in the case of crossed-multilevel modeling described above. It is also possible, to specify an equivalent three-level model for Equation (7) and Equation (11), where

students are nested within each of the transition groups, and the transition groups are nested within each of elementary schools.

REFERENCES

Aitkin, M. and Longford, N. (1986). Statistical modeling issues in school effectiveness studies. **Journal of the Royal Statistical Society, Series A, 144**, 419-461.

Blyth, D., Simmons, R., and Bush, D. (1978). The transition into early adolescence: A longitudinal comparison of youth in two contexts. **Sociology of Education, 51**, 149-162.

Burstein, L. (1980). The analysis of multi-level data in educational research and evaluation. **Review of Research in Education, 8**, 158-233.

Crockett, L., Peterson, J., Grabner, J., Schulenberg, J., and Ebata, A. (1989). School transitions and adjustment during early adolescence. **Journal of Early Adolescence, 9**, 181-210.

Cronbach, L. (1976). Research on classrooms and schools: Formulation of questions, design and analysis. Occasional paper of the Stanford Evaluation Consortium, School of Education, Stanford University.

de Leeuw, J. and Kreft, I. (1986). Random coefficient models for multilevel analysis. **Journal of Educational Statistics, 11**, 57-85.

Goldstein, H. (1986). Multilevel mixed linear model analysis using iterative generalized least squares. **Biometrika, 73**, 43-56.

Hirsh, B. and Rapkin, B. (1987). The transition to junior high school: A longitudinal study of self-esteem, psychological symptomatology, school life, and social support. **Child Development, 58**, 1235-1243.

Hopkins, K. (1982). The unit of analysis: Group means versus individual observations. **American Educational Research Journal, 19**, 5-18.

Jones, R. and Thornburg, H. (1985). The experience of school transfer: Does previous relocation facilitate the transition from elementary to middle-level educational environments? **Journal of Early Adolescence, 5**, 229-237.

Kang, S. (1992). **A mixed linear model with two-way crossed random effects and estimation via the EM algorithm.** Unpublished doctoral dissertation. East Lansing: Michigan State University.

Midgley, C. and Feldlaufer, H. (1987). Students' and teachers' decision making fit before and after the transition to junior high school. **Journal of Early Adolescence, 7**, 225-241.

Rasbash, J. and Goldstein, H. (1994).Efficient analysis of mixed hierarchical and cross classified random structures using a multilevel model. **Journal of Educational and Behavioral Statistics, 19**, 337-350.

Raudenbush, S. (1993). A crossed random effects model for unbalanced data with applications in cross-sectional and longitudinal research. **Journal of Educational Statistics, 18**, 321-349.

Raudenbush, S. and Bryk, A. (1986). A hierarchical linear model for studying school effects. **Sociology of Education, 59**, 1-7.

Robinson, W. (1950). Ecological correlations and the behavior of individuals. **American Sociological Review, 15**, 351-357.

Rosenberg, M. (1965). **Society and the adolescent self-image.** Princeton: Princeton University Press.

Simmons, R., Bylth, D., Van Cleave, E., and Bush, D. (1979). Early entry into adolescence:

The impact of school structure, puberty, and early dating on self-esteem. American Sociological Review, 44, 948-967.

Appendix 1

Component items of students' perception on self-esteem (Base year)

Items	Labels	Internal consistency
BYS44B	I don't have enough control over my life	α = .78
BYS44D	I'm a person of worth, equal to others	
BYS44E	I am able to do things as well as others	
BYS44G	Plans hardly work out, makes me unhappy	
BYS44H	On the whole I am satisfied with myself	
BYS44I	I certainly feel useless at times	
BYS44J	At times I think I am no good at all	
BYS44L	I feel I do not have much to be proud of	
BYS56C	Students in class see R as good student	
BYS56D	Students in class see R as inportant	

Component items of students perception on self-esteem (First follow-up)

Items	Labels	Internal consistency
F1S62B	R doesn't have enough control over life	α =.81
F1S62D	R feels he/she is a person of worth	
F1S62E	R able to do things as well as others	
F1S62G	R feels plans hardly ever work out	
F1S62H	On the whole R's satisfied with self	
F1S62I	R feels useless at times	
F1S62J	At times, R thinks he is no good at all	
F1S62L	R doesn't have much to be proud of	
F1S62D	Students think R is a good student	
F1S67E	Students think of R as important	
F1ESTEEM	Composite of F1 self-esteem scores	

Table 1a Summary of descriptive statistics of individual-level predictor variables(N=483)

Variables	Mean	Std.Dev.	minimum	maximum
FIESTEEM (First follow-up self-esteem)	-.29	3.22	-15.62	14.64
BYESTEEM (Base year self-esteem)	.09	3.14	-11.17	18.24
CSEX(sex)	.03	1.00	-1.00	1.00
NFAMCOMP (Family composition (centered))	.00	.38	-.82	.18

Table 1b Summary of descriptive statistics of group-level predictor variables(N=133)

Variables	Mean	Std Dev	Minimum	Maximum
BYSC17_1 (#Full time regular teachers)	3.77	1.74	1.00	8.00
G8LUNC_1 (Percent of free lunch in school)	3.38	1.98	.00	7.00
G8TYPE1 (Grade span ; p,k,or 1-8)	.16	.37	.00	1.00
G8TYPE2 (Grade span ; 3,4 or 5,8)	.08	.28	.00	1.00
G8TYPE3 (Grade span ; 6-8)	.29	.46	.00	1.00
G8TYPE4 (Grade span ; 7-8)	.22	.41	.00	1.00
NF1C9_1 (#minutes in average class period)	3.38	1.08	1.00	5.00
DSIZE (school size difference)	1.41	2.76	-5.00	8.00

Table 2 Variance decomposition of student's self-esteem

	estimates
within transition group	10.391
middle school	3.254
high school	3.19
transition group	3.998

-2log(likelihood) = 2589.7079

Table 2a Summary of Marginal transition effects

Random effects	Mean	Std Dev	Minimum	Maximum
Middle School Effects	-.01	.56	-2.60	1.48
High School Effects	.02	.54	-2.55	1.44
Transition Group Effects	.01	.68	-3.06	1.73
Marginal Transition Effects	.02	1.29	-4.96	3.34

Table 3 Results of CMM analysis using base year self-esteem

	Variables	estimates	SE	t
[Fixed Effects]				
	Intercept	-.288	-	-
	Byesteem	.211	.046	4.643

[Random Effects]	estimates
within transition group	9.872
middle school	2.956
high school	2.951
transition group	3.615

-2log(likelihood) = 2563.8504

Table 3a Summary of Net transition effects

Random effects	Mean	Std Dev	Minimum	Maximum
Middle School Effects	-.01	.53	-2.55	1.41
High School Effects	.01	.52	-2.54	1.41
Transition Group Effects	.01	.63	-2.98	1.65
Net Transition Effects	.01	1.22	-4.87	3.05

Table 4 Results of CMM analysis using individual-level predictors

	Variables	estimates	SE	t
[Fixed Effects]				
	intercept	-.273	-	-
	byesteem	.21	.045	4.624.
	sex	-.278	.142	-1.946
	family composition	.401	.373	1.072

[Random Effects]	estimates
within transition group	9.77
middle school	2.939
high school	2.918
transition group	3.608

-2log(likelihood) = 2559.1886

Table 4a Summary of total adjusted transition effects

Random effects	Mean	Std Dev	Minimum	Maximum
Middle School Effects	-.01	.53	-2.52	1.52
High School Effects	.01	.52	-2.50	1.50
Transition Group Effects	.01	.64	-2.96	1.78
Total Adjusted Transition Effects	.01	1.23	-4.89	3.20

Table 5 Results of CMM analysis using both individual and group-level predictors

	Variables	estimates	SE	t
[Fixed Effects]	intercept	-1.205	-	-
group-level variables	bysc17	-0.032	0.11	-0.289
	g8lunch	-0.038	0.084	-0.458
	g8type1	0.949	0.55	1.723
	g8type2	0.036	0.604	0.06
	g8type3	1.345	0.422	3.185
	g8type4	0.691	0.454	1.521
	nf1c9	0.168	0.154	1.091
	dsize	-0.092	0.065	-1.415
student-level variables	byesteem	0.207	0.046	4.516
	csex	-0.281	0.144	-1.948
	famcomp	0.387	0.374	1.035

[Random Effect]	estimates
within transition Group	9.719
middle school	2.875
high school	2.853
transition group	3.545

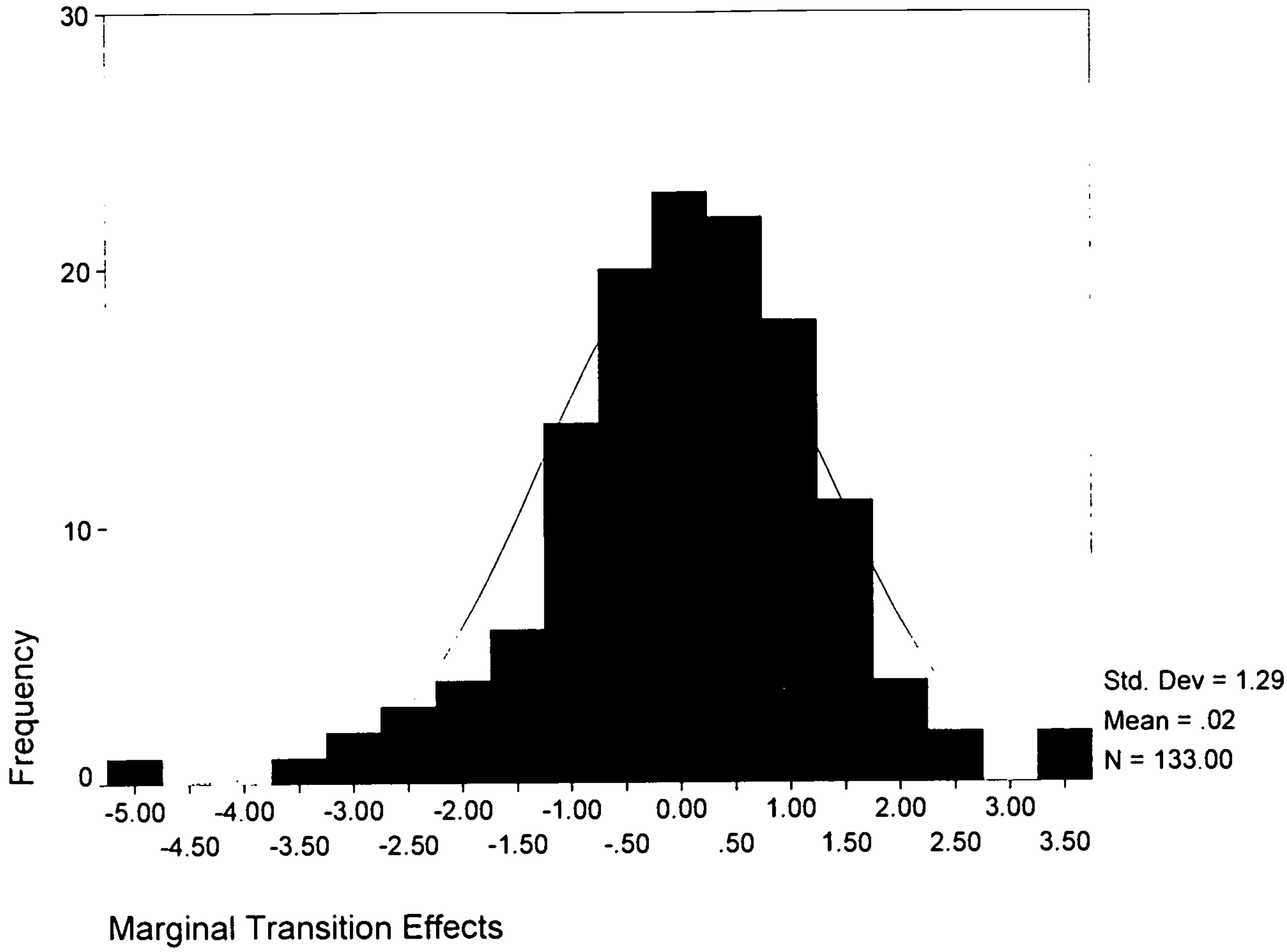
- 2log(likelihood) = 2555.0782

Table 5a Summary of Type A & Type B transition effects

Random effects	Mean	Std Dev	Minimum	Maximum
Middle School Effects	-.01	.50	-2.48	1.36
High School Effects	.02	.50	-2.45	1.34
Transition Group Effects	.02	.62	-2.91	1.60
Type-A Transition Effects	.92	1.38	-4.29	4.60
Type-B Transition Effects	1.05	1.37	-4.10	4.80

Figure 1

Histogram of Marginal Transition Effects



BEST COPY AVAILABLE

Figure 2

Histogram of Net Transition Effects

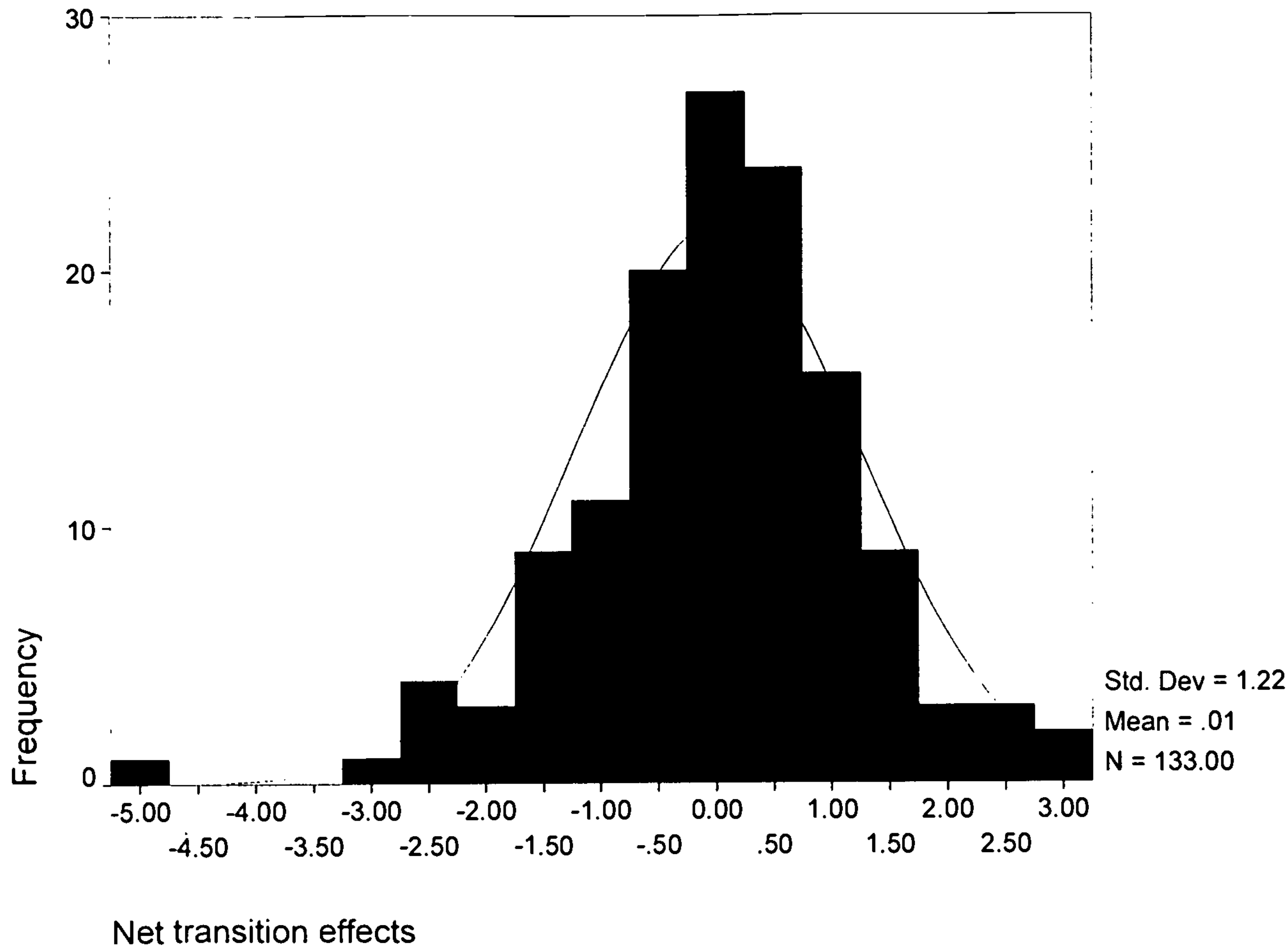
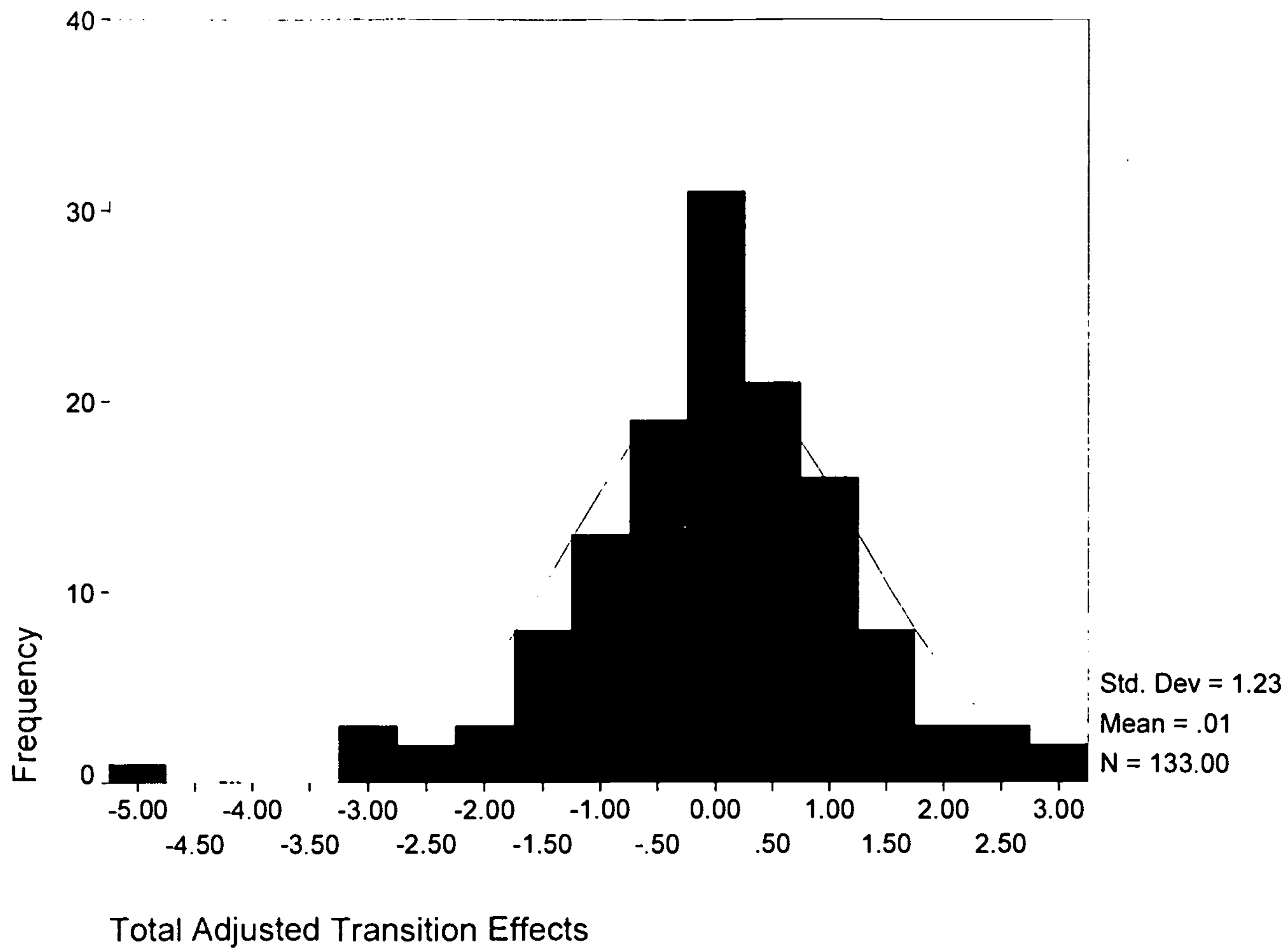


Figure 3

Histogram of Total Adjusted Transition Effects



BEST COPY AVAILABLE

U.S. Department of Education
Office of Educational Research and Improvement (OERI)
Educational Resources Information Center (ERIC)

ERIC®

REPRODUCTION RELEASE

(Specific Document)

I. DOCUMENT IDENTIFICATION:

Title: Multilevel Models for studying Organizational Transition Effects

Author(s): KANG, SANG-JIN

Corporate Source:

Publication Date:

II. REPRODUCTION RELEASE:

In order to disseminate as widely as possible timely and significant materials of interest to the educational community, documents announced in the monthly abstract journal of the ERIC system, *Resources in Education* (RIE), are usually made available to users in microfiche, reproduced paper copy, and electronic/optical media, and sold through the ERIC Document Reproduction Service (EDRS) or other ERIC vendors. Credit is given to the source of each document, and, if reproduction release is granted, one of the following notices is affixed to the document.

If permission is granted to reproduce and disseminate the identified document, please CHECK ONE of the following two options and sign at the bottom of the page.

Check here For Level 1 Release:	The sample sticker shown below will be affixed to all Level 1 documents	The sample sticker shown below will be affixed to all Level 2 documents	Check here For Level 2 Release:
☑ Permitting reproduction in microfiche (4" x 6" film) or other ERIC archival media (e.g., electronic or optical) *and* paper copy.	PERMISSION TO REPRODUCE AND DISSEMINATE THIS MATERIAL HAS BEEN GRANTED BY Sample TO THE EDUCATIONAL RESOURCES INFORMATION CENTER (ERIC)	PERMISSION TO REPRODUCE AND DISSEMINATE THIS MATERIAL IN OTHER THAN PAPER COPY HAS BEEN GRANTED BY Sample TO THE EDUCATIONAL RESOURCES INFORMATION CENTER (ERIC)	☐ Permitting reproduction in microfiche (4" x 6" film) or other ERIC archival media (e.g., electronic or optical), but *not* in paper copy.
	Level 1	Level 2	

Documents will be processed as indicated provided reproduction quality permits. If permission to reproduce is granted, but neither box is checked, documents will be processed at Level 1.

"I hereby grant to the Educational Resources Information Center (ERIC) nonexclusive permission to reproduce and disseminate this document as indicated above. Reproduction from the ERIC microfiche or electronic/optical media by persons other than ERIC employees and its system contractors requires permission from the copyright holder. Exception is made for non-profit reproduction by libraries and other service agencies to satisfy information needs of educators in response to discrete inquiries."

Sign here→ please

Signature:	Printed Name/Position/Title: Sang-Jin Kang / Professor	
Organization/Address: Department of Education, College of Education Yonsei University, Seoul 120-749, Korea	Telephone: +82-2-361-3181	FAX: +82-2-313-2158
	E-Mail Address: sjkang@bubble.yonsei.ac.kr	Date: 11/17/97

EA 028 844

III. DOCUMENT AVAILABILITY INFORMATION (FROM NON-ERIC SOURCE):

If permission to reproduce is not granted to ERIC, *or*, if you wish ERIC to cite the availability of the document from another source, please provide the following information regarding the availability of the document. (ERIC will not announce a document unless it is publicly available, and a dependable source can be specified. Contributors should also be aware that ERIC selection criteria are significantly more stringent for documents that cannot be made available through EDRS.)

Publisher/Distributor:
Address:
Price:

IV. REFERRAL OF ERIC TO COPYRIGHT/REPRODUCTION RIGHTS HOLDER:

If the right to grant reproduction release is held by someone other than the addressee, please provide the appropriate name and address:

Name:
Address:

V. WHERE TO SEND THIS FORM:

Send this form to the following ERIC Clearinghouse:

ERIC Clearinghouse on Educational Management
1787 Agate Street
5207 University of Oregon
Eugene, OR 97403-5207

However, if solicited by the ERIC Facility, or if making an unsolicited contribution to ERIC, return this form (and the document being contributed) to:

ERIC Processing and Reference Facility
1100 West Street, 2d Floor
Laurel, Maryland 20707-3598

Telephone: 301-497-4080
Toll Free: 800-799-3742
FAX: 301-953-0263
e-mail: ericfac@inet.ed.gov
WWW: http://ericfac.piccard.csc.com